Research in International Business and Finance 37 (2016) 78–92

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Does high frequency algorithmic trading matter for non-AT investors?

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ARTICLE INFO

Article history:
Received 16 July 2015
Received in revised form 15 October 2015
Accepted 16 October 2015
Available online 6 November 2015

Keywords:
Algorithmic trading
Non-algorithmic investors
Volatility
Spatial econometrics

ABSTRACT

The extant literature has typically measured the impact of high frequency algorithmic trading (HFT) on short term outcomes, in seconds or minutes. We focus on outcomes of concern for longer term non-algorithm investors. We find in some cases HFT increases volatility arising from news relating to fundamentals. Furthermore HFT is associated with the transmission of that volatility across industries, and that transmission is based on short term correlations. Finally, we find that the period since the introduction of algorithmic trading (AT) has seen increases in both the variances and covariances of return volatility in most industries. However increases in the variances has not been uniform in that it has fallen sharply in a few industries. The magnitudes are such that, overall, AT has coincided with reduced return volatility variance.

1. Introduction

Algorithmic trading in asset markets has risen in importance since its introduction in the mid-1990s, revolutionizing the way market transactions are conducted. While the underlying strategies used by algorithms to transact assets might follow the same logic as human traders, two important differences set them apart. First, algorithmic trading can take into account much more information than a human trader alone could process in the time needed to make a given decision to transact. Second, while human traders may make transaction decisions based primarily on a particular rule, just as an algorithm would, in addition to this rule humans intuitively defer to an amorphous set of parameters, which taken together, we think of as human judgment.

It is difficult to program all elements of human judgment into trading algorithms, and so in practice firms use a mix of algorithms and human judgment (CFTC and SEC, 2010). Even in fully automated transactions, where not only the actual timing and carrying out of the transaction, but even the decision to transact is driven by an algorithm, there are pauses built into the system so that if there is any doubt about the quality of data, price, or quantity of transactions in the marketplace, the system stops for human input to move forward. This was illustrated rather dramatically during the “flash crash” of May 2010 when many traders withdrew from the markets as their automated systems paused for human input due to unusual market fluctuations.

Empirical studies of algorithmic trading (and a subset called high frequency trading, on which we concentrate in this paper), have estimated its impact on various aspects of market quality such as liquidity, price spreads, the extent of adverse

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http://dx.doi.org/10.1016/j.ribaf.2015.10.014
0275-5319/

selection, trade-related price discovery, and the volatility of asset prices. This body of work has typically considered the impact of AT on short term outcomes taking place in seconds or minutes.

This leaves open the question of the effect of those AT strategies on non-AT investors that accept the risk of ownership in listed companies for extended periods of time. For these longer term investors the benefits of stock investments relate to compound asset returns which are reduced by volatility – see Booth and Fama (1992). Moreover volatility itself might be a deterrent to investment for many non-AT investors. The literature has found mixed and sometimes contradictory results when it comes to the impact of AT on volatility.

Our paper contributes to the literature by focusing on volatility's relation with one of the most common and widespread HFT strategies, namely statistical arbitrage. Under this strategy HFT uses short term price correlations to predict price movements and trade to profit from them. We use the technique of spatial econometric modelling to test the hypothesis that statistical arbitrage could lead to volatility being transmitted or spilling-over across stocks. Intuitively, if statistical arbitrage makes bets that a stock will move simply because another, or a group of other stocks moved then this could often cause price movements unrelated to fundamentals, and raise volatility.

Our data covers the period May 1985–May 2012 at daily frequency. Since we are measuring volatility at the daily frequency our interest lies primarily with strategies employed by the subset of algorithmic traders referred to as high frequency traders (HFT). These traders hold their position only for a short period of time and usually end the day in a neutral position. We measure of HFT by its share of the total trades that take place.

We first describe our return volatility data at the industry level. Specifically, we describe the changes since the introduction of AT in the variance, as well as the covariances of return volatilities among companies within each of 35 industries. We then focus on the level of return volatility itself. We specify a formal spatial model which relates the level of return volatility in each of 35 industries to volatility transmitted from other industries, as well as to macroeconomic and industry fundamentals.

Our results indicate that stock price volatilities in a given industry significantly spill-over to other industries, and these spill-over effects are not uniform. Furthermore, these volatility spill-overs have been significantly affected by the advent of HFT. Since HFT has increased over the years, its effects on industry volatility spill-overs has become more dramatic over time. As one might expect, we find that the relationship between stock price volatility and stock price fundamentals has mostly weakened with the increase in HFT. On another issue, AT has coincided with an increase in the variance of stock price volatility in all except two industries which relate to petroleum. In addition AT has also coincided with an increase in the covariances between stock price volatility within our considered industries.

HFT has made rapid progress in technology and this has led to an arms-race among participants for acquiring the fastest and most efficient algorithms and machines. As a side-effect, increased competition has eroded HFT profits. Regulators have also clamped down on HFT, following accusations of market manipulation. Market manipulation once thought of as a predominantly developing market issue (Azad et al., 2014) has now featured quite prominently in developed countries via HFT. One of the outcomes of this scenario is that HFT is resorting to high risk strategies in hopes of making profits (Philips, 2013). Naturally for the markets a whole this might imply higher probability of volatility and chaos. Particularly vulnerable might be those financial sectors where regulation has failed to make appropriate inroads. An example of such a sector is shadow banking. In this sector financial entities are not governed by traditional banking regulation but they nonetheless engage in activities that are similar to banks and thus carry the same risks. An example of such bank-like activities is that shadow banking entities raise money by short-term borrowing and hope to leverage that by using the funds to buy and make a profit on longer term securities. Thus any excess volatility that arises from risky HFT strategies can easily upset shadow banking by causing fluctuations in the price of securities in which it deals. When such troubles arise, shadow banking entities do not have the fall-back option of borrowing from the Federal Reserve and neither are their investors protected by deposit insurance. In addition, given that shadow banks may be partly owned by banks, these troubles can propagate to the formal banking sector as well. Thus both the risky behaviors of HFT and the resulting vulnerabilities seem to be on the rise.

A brief review of relevant literature follows in Section 2. Data descriptions are given in Section 3. Our discussion of return volatility variances and covariances within industries is given in Section 4. Corresponding empirical results are given in Section 5. The spatial model is specified in Section 6, and empirical results relating to it are given in Section 7. A summary and conclusions are given in Section 8.

2. Review of literature

As suggested, studies of asset price volatility typically have a high frequency and short time-sample focus. For example, Hasbrouck and Saar (2011) measured short term market volatility as price volatility in 10-min intervals and found that algorithmic trading, which they referred to as low-latency trading, reduced volatility. Their sample period consisted of two months, specifically, the relatively normal month of October 2007 and the heightened uncertainty month of October 2008, which was right after the fire sale of Bear Sterns. They found that algorithmic trading reduced volatility in both time periods. On the other hand, Brogaard (2010) studied the volatility impact of high frequency trading, which is the subset of algorithmic trading which holds its position only for a short period of time and ends the day in a neutral position. He used data on 10 s realized volatility for each stock of the 120 Nasdaq stocks which was selected to represent a wide range of sizes, industries and listing venues. His data covered 5 days from February 22 to 26, 2010. He found that the proportion of high frequency trading in total trades' value and volatility were not contemporaneously related. Hendershott and Riordan (2011)